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A COGNITIVE KNOWLEDGE-BASED FRAMEWORK FOR SOCIAL AND METACOGNITIVE SUPPORT IN MOBILE LEARNING

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ABSTRACT

Aim/Purpose	This work aims to present a knowledge modeling technique that supports the representation of the student learning process and that-is capable of providing a means for self-assessment and evaluating newly acquired knowledge. The objective is to propose a means to address the pedagogical challenges in m-learning by aiding students' metacognition through a model of a student with the target domain and pedagogy.
Background	This research proposes a framework for social and meta-cognitive support to tackle the challenges raised. Two algorithms are introduced: the meta-cognition algorithm for representing the student's learning process, which is capable of providing a means for self-assessment, and the social group mapping algorithm for classifying students according to social groups.
Methodology	Based on the characteristics of knowledge in an m-learning system, the cognitive knowledge base is proposed for knowledge elicitation and representation.

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	The proposed technique allows a proper categorization of students to support collaborative learning in a social platform by utilizing the strength of m-learning in a social context. The social group mapping and metacognition algorithms are presented.
Contribution	The proposed model is envisaged to serve as a guide for developers in implementing suitable m-learning applications. Furthermore, educationists and instructors can devise new pedagogical practices based on the possibilities provided by the proposed m-learning framework.
Findings	The effectiveness of any knowledge management system is grounded in the technique used in representing the knowledge. The CKB proposed manipulates knowledge as a dynamic concept network, similar to human knowledge processing, thus, providing a rich semantic capability, which provides various relationships between concepts.
Recommendations for Practitioners	Educationist and instructors need to develop new pedagogical practices in line with m-learning.
Recommendation for Researchers	The design and implementation of an effective m-learning application are challenging due to the reliance on both pedagogical and technological elements. To tackle this challenge, frameworks which describe the conceptual interaction between the various components of pedagogy and technology need to be proposed.
Impact on Society	The creation of an educational platform that provides instant access to relevant knowledge.
Future Research	In the future, the proposed framework will be evaluated against some set of criteria for its effectiveness in acquiring and presenting knowledge in a real-life scenario. By analyzing real student interaction in m-learning, the algorithms will be tested to show their applicability in eliciting student metacognition and support for social interactivity.

Keywords m-learning, pedagogy, mobile device, knowledge modeling

INTRODUCTION

Mobile technology has grown significantly in recent years; developers agree with the term *mobile first*. Most work nowadays is done using smartphones. Cell phones are excellent communication and social tools which have become a source of unlimited entertainment. Mobile technology also impacts the way people do business and marketing, through knowledge creation and an infinite amount of information exchange. Mobile devices extend the capability of cell phones beyond just verbal communication, accomplishing a variety of different communicative tasks (Ishii, 2006). The popularity of mobile devices and social networking sites which affect various aspects of daily life is unlikely to diminish. Mobile technology has a potential to disrupt most traditional models of doing business, and education is one industry that will most notably be impacted. Thus, focusing on the effects of these devices and services on student learning is of importance. The rapid development of mobile learning has a significant impact on education (Klaßen, Eibrink-Lunzenauer, & Glöggler, 2013). Mobile learning potentially places educational institutions at the forefront of pedagogical practice and addresses students' requirements for flexibility and ubiquity. This urges researchers to re-conceptualize the role of teachers in the learning process and to investigate the impact of using m-learning to support student learning and to help educators to adopt the mobile learning environment. As we move into the knowledge society, new interactive technologies are providing us with both challenges and opportunities. The challenge is to find out how to construct environments that provide and support different kinds of learning. The opportunity is to drastically change the existing learning process to give students a much higher degree of individual support and a flexible approach to managing their learning experiences. Thus, many researchers, as well as academic and industrial practitioners, are currently exploring the potential of mobile devices in supporting the learning process.

Mobile learning (M-learning) is *an educational interaction delivered through mobile technology and accessed by students from any location* (Traxler, 2009). M-learning is also viewed as the use of mobile devices with an Internet connection for educational purpose (Kinash, Brand, & Mathew, 2012). Most literature indicates that m-learning has offered considerable benefits to building and supporting creative, collaborative, interactive capacities within the learning environments, helping in the creation of knowledge. Several authors referred to mobile learning ability to enhance collaborative learning (A. Barker, Krull, & Mallinson, 2005; Cheon, Lee, Crooks, & Song, 2012; Picek & Grčić, 2013). Moreover, some of the m-learning benefits include allowing data and information collection, enhancing and building knowledge and providing necessary support by integrating work activities and students' experiences in learning (Alhazmi, Rahman, & Zafar, 2014; Sharples, 2006).

As m-learning uses a variety of devices, it is agreed that m-learning introduces a globally *flexible learning approach*. Some studies have highlighted some advantages of m-learning such as extending learning and teaching beyond traditional teacher-centered classroom (Ktoridou, Gregoriou, & Eteokleous, 2007); providing flexible learning environments anytime anywhere, generating new technology-enhanced learning; allowing new modes of teaching; and encouraging students' active participation and collaboration (Guy, 2010; Ktoridou et al., 2007; Picek & Grčić, 2013). Additional benefits of m-learning are cost effectiveness (Pollara, 2011), and game learning (Kadirire & Guy, 2009).

The unique advantages of an m-learning platform are mobility (Sharples, Sánchez, Milrad & Vavoula, 2008), access (Parsons & Ryu, 2006), and ubiquity (Kukulska-Hulme, Sharples, Milrad, Arnedillo-Sánchez, & Vavoula, 2009). According to (Sharples et al., 2008), m-learning is characterized by physical mobility in its flexibility of time, place, pace, and space. Klopfer, Squire, and Jenkins (2002) addressed some attributes that made m-learning interesting for teaching and learning. Those attributes are portability, connectivity, social interactivity, individuality, and merging digital and physical worlds (Klopfer et al., 2002). Hu and Webb (2009) demonstrated that m-learning would allow access to learning materials anytime, anywhere, which helps to improve students' learning outcomes and makes learning more personalized (Schofield, West, & Taylor, 2011), to provide quick access to information, and to provide opportunities for individualized, collaborative, and informal learning (Cheon et al., 2012).

This work aims to present a knowledge modeling technique that supports the representation of the student learning process and that is capable of providing a means for self-assessment and evaluating newly acquired knowledge. The objective is to propose a means to address the pedagogical challenges in m-learning by aiding student metacognition through a model of a student with the target domain and pedagogy. The proposed technique allows a proper categorization of students to support collaborative learning in a social platform, utilizing the strength of m-learning in a social context. In the next section, we review m-learning theories, frameworks, and challenges. The third section discusses knowledge modeling and manipulation techniques, highlighting the advantages and disadvantages of different approaches. The proposed knowledge-based framework for m-learning is presented in the fourth section, followed by the conclusion.

M-Learning Theories, Frameworks and Challenges

Learning Theories

Learning as defined by Greeno, Collins, and Resnick (1996) is a "constructive process of conceptual growth" (p. 16), which sometimes requires restructuring of concepts based on the learners understanding and the development of their cognitive abilities. Over the past decades, researchers have developed various learning theories in an attempt to explain how knowledge is acquired. These include theories such as behaviorism, cognitivism, and constructivism.

Behaviorism has been the dominant approach to learning. This method was used in developing curriculum and served as the foundation for educational technology (Gillani, 2006; Kaya, 2011). The behavioristic approach was concerned with prescribing steps, procedural sequences, and a strict systematic, structured approach to the design and development of educational technology programs (Gillani, 2006, p. 119). Even though this method described how behavior got transformed, it did not explore the mental processes going on in a human's mind that accounted for how conceptual change occurs (Kaya, 2011).

The cognitive learning perceptive is centered on the basis that attaining knowledge is the foundation of learning. Any new data acquired by an individual is expected to be used in diverse circumstances. How well this knowledge is applied depends on how it is understood and stored in the individual's long-term memory (Schneider & Stern, 2010). The foundation of the cognitive theory is based on Piaget's theory of cognitive development and Vygotsky's theory on social cognitivism. Piaget discusses the concept of schemata, while Vygotsky focused on explained learning that later gave birth to the idea of scaffolding (Kaya, 2011; Thomas, 2011).

Piaget's theory, which explained the various circumstances an individual develops and learns new ideas, provides a framework for educators to analyze and design educational environments to assist learners in constructing their knowledge. He did not provide specific processes for teaching but offered some guiding principles upon which educational activities can be designed and planned. Invariably, he provided a learning environment where teachers can discover and build their teaching procedure and approach. Cognitive psychologists regarded learning as a changing process in which the learners build their knowledge through interaction with the environment. They suggest that the role of teachers is not to enforce steps, processes, and a rigid framework, but instead to construct learning environments that will aid students in forming their own (Kaya, 2011). The influence of cognitive theories on education can be seen in the emergence of various teaching methods. These methods, as described by Kaya (2011), are a cognitive apprenticeship, reciprocal teaching, anchored instruction, inquiry learning, discovery learning, and problem-based learning. The cognitive apprenticeship method was developed based on Vygotsky's theory of zone of proximal development. This process involves aiding students in understanding concepts and procedures under the guidance of an expert. Reciprocal teaching is based on one of the branches of cognitive learning known as information processing. It involves an instructional activity where the teacher dialogues with the student to promote an understanding of the instruction material. In this method, cognitive techniques such as modeling, scaffolding, coaching, and fading are used. Anchored instruction concerns the design and implementation of educational guidelines around anchors, which are mostly stories, adventures, or situations involving a problem or issue to be sorted out, that is of interest to the student. It is problem-based and technology driven learning in which interactive materials assist as anchors. The anchored instruction method of teaching stresses the need to offer students a chance to think and work on problems as supported by cognitive constructivism.

Inquiry learning evolved from Piaget's theory of cognitive development. It is aimed at aiding students in developing their higher-order thinking abilities. Students engage in inquiry learning through the course of investigating or trying a hypothesis to discover solutions to a problem. With this approach, students take ownership of their learning. Like inquiry learning, discovery learning was formed based on Piaget's theory of cognitive development. It is defined as an approach to teaching where students interact with their environment by discovering and deploying objects, tussling with questions and arguments, or carrying out experiments. This method of allowing an individual to make discoveries teaches one to obtain information in a manner that makes it readily available in problem-solving. The problem-based learning approach deals with providing students with an ill-structured problem with various possible solutions and requiring them to find answers to the problem. This method provides the problem at the beginning and expects students to solve it based on existing knowledge as opposed to traditional teaching where the facts are introduced before the problem (Kaya, 2011).

The cognitive approach places the learner and the internal mental processes at the center of teaching. Because cognitivism focuses on revealing the various processes involved in knowledge acquisition, thereby providing strategies that support students learning, tutors can utilize this in their effort to aid students in attaining their goals.

M-LEARNING MODELS AND FRAMEWORKS

The advancement in mobile computing has nurtured the research and implementation of projects on advancing mobile learning experiences for diverse learners (Hsu & Ching, 2015). This has encouraged the development of various m-learning models and frameworks. Frameworks describe the conceptual interactions among components and ideas based on related concepts, while models represent descriptive representation of associations among elements in a framework according to the investigation of empirical data (Hsu & Ching, 2015). In this section, we review some proposed m-learning models and frameworks.

Koole (2009) developed the Framework for Rational Analysis of Mobile Education (FRAME), which defines m-learning as a convergence of mobile technology, human learning abilities, and social interaction. The framework considers some technical characteristics of mobile devices and the personal and social aspects of learning. FRAME involves concepts similar to Vygotsky's activity theory and supports constructivism. Koole's framework aims to address the issue of information overload, knowledge navigation and collaborative learning (Koole, 2009). It provides a guide for developing future mobile devices and m-learning curricula. Ng and Nicholas (2013) adopted the framework for the sustainability of information and communication technology (ICT) in education for m-learning in schools. It involved some personal and non-personal components. The personal elements of the framework included stakeholders such as teachers, students, parents, leadership, and management. While the non-personal components comprise of pedagogy, mobile devices, infrastructure, and interactions between the stakeholders (Hsu & Ching, 2015). The proposed framework enables the exploration of interactions between stakeholders and the technology.

The activity theory was applied by Uden (2006) to design a framework for understanding the components of a task in a context-aware mobile learning system. The proposed framework suggests that the design of an activity-based mobile learning application should follow these steps: 1) explain the aim and motive of the activity; 2) analyze the learning content; 3) have a historical analysis of the activity and its features; 4) search for internal inconsistencies. This approach offers a full view of the dynamic nature of mobile learning activity. Motiwalla (2007) proposed an application framework for m-learning that is aimed at providing a better understanding of the strengths and weaknesses of technology and its integration with appropriate pedagogical principles. It integrates the concepts from mobile connectivity and e-learning, to form application requirements for mobile learning (Motiwalla, 2007). The framework addresses the technical features which support content delivery, personalization and collaboration in m-learning. Sha, Looi, Chen, and Zhang (2012) proposed a self-regulatory learning (SRL) model of mobile learning. It is aimed at explaining the concepts, mechanism, and process of mobile learning with its inherent relationship with SRL (Sha et al., 2012). Due to the ubiquity and flexibility of m-learning, Sha et al. (2012) suggested that learners should be responsible for their education in m-learning, as compared to other forms of learning. Thus, in their proposed model, self-regulation functions as a learning agent facilitated by mobile devices, while the mobile devices serve as tools for providing social and pedagogical support during the learning process (Hsu & Ching, 2015).

M-LEARNING CHALLENGES

Designing and developing an efficient m-learning application within an educational environment is still a challenge to most educators due to the complex environment that incorporates many pedagogical and technological elements. Although m-learning offers many benefits, there are some crucial issues related to using mobile technology in education. These challenges include management problems, design and development challenges, cultural and social challenges, and evaluation challenges.

Management challenges

Little is known about how educational institutions can use mobile devices to support teaching and learning practices (Zeng & Luyegu, 2011). A study conducted by Adeyeye, Musa, and Botha (2013), found that the support given to m-learning projects from the educational institutions affects the success or failure of these projects. It is important for educational institutions to manage such change through innovation, defining new policies, and creating awareness among stakeholders in the future m-learning implementation. One of the most critical challenges facing the education institutions when implementing an m-learning project is managing the change within the organization. Also, educational institutions need to define an explicit policy, device availability, and technical and pedagogical support, to achieve wide-scale implementation of m-learning. Also, Ismail, Azizan, and Azman (2013) and Tai and Ting (2011) noted that the participation of teachers and their belief in the possibilities that m-learning offers in enhancing learning would help in successful implementation.

Design and development challenges

It is challenging to develop an m-learning application that truly supports teaching and learning, to achieve educational objectives and institutional goals. The phases of a mobile learning project are similar to those in any other project which includes analysis, design, development, operation, and evaluation. M-learning projects need analysis similar to e-learning projects with some specific considerations of mobile learning features and capabilities (Buff, 2013).

Mobile devices are more than just a phone; they are equipped with various capabilities and features that could be used to enhance teaching and learning. These capabilities are not limited to a camera, calculator, readers, geo-location, capture, recording, document review, sensors, the Internet, search, media player, notifications, calendar, cloud storage, touch screen, or messaging. Understanding the capabilities of mobile devices will help designers and developers to explore the potential of m-learning. However, there are some technical concerns related to the device that must be considered when designing and developing m-learning applications. Park (2011) listed some technical limitations related to the physical attributes of mobile devices, such as small screen size, insufficient memory, limited battery, network reliability, excessive screen brightness outside, limitation of software applications, safety, and privacy. Technical limitation such as low bandwidth on wireless networks was also reported (Franklin, Sexton, Young, & Ma, 2007; Newhouse, Williams, & Pearson, 2006). Kadirire and Guy (2009) also note the barriers related to the different operating systems for mobile learning.

Social and cultural challenges

The interaction between culture and technology must be considered when introducing new technology to an existing social environment. There is a need to study the proper use of these new technological tools, considering its possible impact in transforming cultural practices. Mobile technologies and applications provide distinctions between the new m-learning environments and the traditional classroom learning, which generates new learning and teaching opportunities.

Cultural considerations increase the complexity of designing learning interfaces because more variables are added. Introducing learning applications to a new culture brings many issues that need to be investigated. It is vital first to understand the nature of the target students' culture and to use the findings as a basis for the design of the application (Al-Hunaiyyan, 2000). It is evident that the knowledge and cultural aspects have a direct impact on instructor's personality in the m-learning environment. Instructors facilitate, lead, guide, supervise, monitor, and evaluate the educational process in the learning environment. The instructor should possess the knowledge, insight and intelligence to understand the cultural background of his students and to determine the proper method to handle them individually.

Evaluation and quality assurance challenges

Evaluation is necessary for the lifecycle of interactive systems design, and m-learning systems include challenges of evaluating both the technology and the learning outcome. Evaluation is both formative and summative, occurring during the production of the application and after the delivery evaluation (Laurillard, 1994). Furthermore, P. Barker, Giller, Richards, and King (1993) state that the assessment can involve a range of different dimensions, such as learning effectiveness, interactivity, user-friendly interface, and the quality of education. The development of evaluation strategies for education has focused on face-to-face contact with students in classrooms, using questionnaires, interviews, and focus groups. Now, e-learning and m-learning add complexity to the evaluation process and force educational institutions to consider m-learning technical features, social norms, and pedagogical theories including learning strategies, learning outcome, engagement, collaboration, and ubiquity.

Regarding the evaluation of an m-learning system, Messinger (2011) states that there is a lack of evidence regarding the efficient use of mobile devices in the classroom, thus limiting the widespread adoption of mobile learning. He emphasizes looking at various methods to evaluate the effectiveness and asks how to assess learning outcome, urges educators, researchers, and policy makers to integrate evaluation and quality assurance into the development and implementations of m-learning technologies. The design, planning, implementation, and evaluation of the use of mobile technologies must be integrated for successful realization and sustainability of an m-learning system.

Pedagogical limitations of m-learning

The primary drivers of innovation should not be just deploying technology; there must be a function of pedagogically sound methodologies that achieve educational objectives. In developing a successful mobile educational application, it is necessary to follow design guidelines and methods for the learning process to fit the use of mobile learning (Committee on Institutional Cooperation [CIC]), 2013). Significant efforts have been made to provide resources and strategies to integrate mobile devices into learning environments (Johnson, Levine, Smith, & Stone, 2010). Dahlstrom, Walker, and Dziuban (2013) suggest that research is needed to understand pedagogical insights that will help instructors better embrace mobile technologies in and out of the classroom. It is suggested that to accomplish this, mobile learning requires a successful integration between content and technology to provide a successful learning environment (CIC, 2013; Duderstadt, 2011; McGreal, 2012).

Mobile technology should be used if it can support student learning and enhance the curriculum during learning experiences by integrating the appropriate learning styles (CIC, 2013). Drenoyianni, Stergioulas, and Dagiene (2008) showed that the effective use of mobile technology is less about tools and more about students' ability to access, manage, and evaluate digital learning materials. Alhazmi and Rahman (2012) argued that the technological features of mobile applications such as usability, flexibility, and interactivity are essential to integrate technology into educational settings successfully; however, pedagogical elements are necessary to enhance the teaching and learning process.

Sharples, Taylor, and Vavoula (2005) argued that, when designing mobile learning applications, we must ask what teaching and learning strategies work best for which technological tools and should also highlight that mobile learning is based on the mobility of students across time, space, and content. Messinger (2012) sees that the lack of practical frameworks in m-learning limits the widespread adoption of mobile learning. Other researchers listed some factors affecting the widespread adoption of mobile learning, such as lack of theoretical and pedagogical grounding and lack of teacher support and training (Cochrane, 2014; Peng, Su, Chou, & Tsai 2009).

Looi, Sun, Seow, and Chia (2014) found limited research on the investigation of curricular based implementations of mobile learning and devices. Park (2011) advised the need for the development of appropriate learning theories to be integrated effectively into the curriculum. The support for instant access to other students and information in m-learning solicits the need for designing applications which promote communication and collaboration. Mobile applications can be designed to support teaching and learning by meeting the unique functional and instructional requirements of adaptive, collaborative, and student-centered features.

In m-learning, students have little knowledge of the delivery of teaching materials and the educational process (Ebrahim, Ezzadeen, & Alhazmi, 2015). This lack of external feedback results in confusion about learning goals and gains. The ability of students to be aware of their learning process (meta-cognition) helps them understand their learning progress and manage their knowledge acquisition process. One of the aims of this research is to propose a knowledge modeling technique that supports the representation of the student learning process, which is capable of providing a means for self-assessment and evaluating newly acquired knowledge. The next section presents and compares various knowledge modeling techniques which can be applied for representing and manipulating the student learning process in m-learning. It is aimed at proposing a suitable knowledge modeling and manipulation technique in m-learning.

KNOWLEDGE BASE MODELING IN M-LEARNING

In m-learning there are several processes which involve accessing various data sources, managing different user profiles, and accessing and integrating with other information systems. The m-learning system consists of an administration module, instructor module, and student module, which requires connections between student records, domain knowledge, and management rules. These attributes justify the consideration of m-learning system as not just a conventional information system, but a knowledge-based system (KBS) (Mohanna, 2015). Previously, KBS development was considered a transfer of human knowledge into a knowledge base (Wielinga, Schreiber, & Breuker, 1992). This view regarded knowledge as an already existing entity that needs to be collected and stored. However, this approach is not suitable for representing different knowledge types (Studer, Benjamins, & Fensel, 1998). Due to the various kinds of knowledge in m-learning system, using the transfer approach makes the maintenance process challenging and time-consuming. Thus, this method is only feasible for small scale prototypes, thereby ushering a shift from the transfer approach to the modeling approach (Ramirez & Valdes, 2012). The modeling approach is not intended to simulate the entire cognitive process of the student, but to produce a model which offers similar results.

In this research, we view knowledge from the *cognitive constructivist* perspective where knowledge is considered a constructed entity represented abstractly in an individual's brain (Fosnot & Perry, 1996; Jonassen & Land, 2012; Yilmaz, 2008). In an m-learning system, knowledge is formed both individually and as a group through students' solution steps, reports, discussions, suggestions, course-related feedbacks, comments, and all other educational types of knowledge generation (Mohanna, 2015). Eliciting this progressive and accumulative knowledge using a proper knowledge base modeling approach will improve the m-learning process. There are various knowledge base modeling and manipulation approaches used to represent knowledge. In the next section, we discuss and compare these different categories of knowledge base modeling and manipulation techniques. This is aimed at identifying a suitable method for modeling knowledge in the m-learning system.

KNOWLEDGE BASE MODELING APPROACHES

According to the theories of knowledge base modeling and manipulation technology, KBS can be categorized as linguistic knowledge bases (Baker, 2014; Fellbaum, 1998; Speer & Havasi, 2012), expert knowledge bases (Driankov, Hellendoorn, & Reinfrank, 2013; Kerr-Wilson & Pedrycz, 2016; Kung & Su, 2007), ontology (Fensel, 2004; Sanchez, Batet, Valls, & Gibert, 2010) and most recently the cognitive knowledge base (Wang, 2014).

Linguistic knowledge base attempts to model human grammar, which is divided into syntax, semantics, phonology, morphology, and the lexicon. Some typical examples of a linguistic knowledge base are *ConceptNet*, *FrameNet*, and *WordNet* (Bimba et al., 2016). *ConceptNet* is a common-sense knowledge base which describes the human knowledge and its expression (Agarwal, Poria, Mittal, Gelbukh, &

Hussain, 2015; Agarwal & Sureka, 2015). It is aimed at eliciting common-sense knowledge that describes the real world (Bimba et al., 2016). Knowledge in *ConceptNet* is represented as graphs, with the nodes indicating concepts which are composed of action verbs (Bicocchi, Castelli, Mamei, & Zambonelli, 2011). By using the theory of frame semantics, *FrameNet* was developed as a lexicon of English language which is understandable by both humans and machines (Bimba et al., 2016). Unlike, *ConceptNet* which represents knowledge in the form of graphs, *FrameNet* represents knowledge in the form of a relationship between frames and an annotated corpus (Baker, 2012; Wandmacher, Ovchinnikova, Mönnich, Michaelis, & Kühnberger, 2011). Frames are structures that describe an object, situation, or event in a script-like form (Ruppenhofer, Ellsworth, Petruck, Johnson, & Scheffczyk, 2006). On the other hand, *WordNet* is a lexical database where words and their meanings are connected to each other through semantic and lexical similarities (Bimba et al., 2016). While *ConceptNet* represents knowledge as graphs and *FrameNet* as frames, WordNet represents knowledge in as a semantic network of *synsets* (Bimba et al., 2016).

An expert knowledge base contains relevant domain knowledge for problem-solving. It represents knowledge in the form of rules. The rules consist of two parts, the antecedent which refers to the IF part, and the consequent representing the THEN part. A rule can have several antecedents which are joined by conjunction (AND) or disjunctions (OR). The antecedent of a rule consists of two parts – a linguistic object and its value – linked by an operator. The operator identifies the linguistic object and assigns a value. Rules can be used to represent relations, recommendations, directives, strategies, and heuristics (Negnevitsky, 2005). Expert knowledge bases are classified as either logical rule-based (LRS) or fuzzy rule-based (FRS) systems (Bimba et al., 2016). In a logical, rule-based system, knowledge is represented as binary logic. If the antecedent is true, then the consequent is also true. However, in a fuzzy rule-based system, if the antecedent is true, the consequent could be partially right. This provides an efficient way to represent continues variables (Banerjee, Jones, & Williams, 2001). In a fuzzy rule-based system, knowledge is represented in the form of fuzzy sets. Fuzzy logic is a method for expressing and applying human understanding in a form which represents imprecise terms such as rarely, sometimes, often, occasionally, etc. (Negnevitsky, 2005).

Ontology is a branch of metaphysics which deals with the nature of being. An ontology represents knowledge as a taxonomy of concepts with their values, attributes, and relations. *Ontology is defined as a formal, explicit specification of a shared conceptualization* (Studer et al., 1998). The main aim of ontologies is to provide a platform that supports sharing and reuse of knowledge in a computational form (Bimba et al., 2016). Ontologies are composed of at least three core elements, which include (1) classes (domain concepts), (2) relations (the relationship between concepts), and (3) instances (real world phenomenon) (Sánchez, 2010). Based on conceptualization and various levels of generality, ontologies can be classified as application ontology, domain ontology, generic ontology, or representation ontology (Bimba et al., 2016). Application ontologies elicit the necessary characteristics needed to describe the relationship between concepts according to a specific task in a particular domain (Liu, Wang & Wu, 2010; Savonnet, Leclercq, & Naubourg, 2016). Alternatively, domain ontologies represent concepts that are only valid in a particular field. They are aimed at unifying concepts and terminologies among members of a certain group who need to share information (Bimba et al., 2016). However, generic ontologies are valid across multiple domains (Ye, Stevenson, & Dobson, 2011). They represent various concepts such as event, state, process, action, etc. Representational ontologies, on the other hand, represent existing objects without explicitly declaring what needs to be represented. They capture knowledge that is independent of the problem-solving methodology (Bimba et al., 2016).

A cognitive knowledge base (CKB) represents knowledge as a formal concept based on an *Object-Attribute-Relation* (OAR) model according to concept algebra (Valipour & Yingxu, 2015). The emergence of a cognitive knowledge base was based on the insufficient operations on acquired knowledge and poor transformability between different knowledge sources (Wang, 2015a). Knowledge in the cognitive knowledge base is manipulated as a dynamic concept network, similar to human knowledge processing (Bimba et al., 2016). A cognitive unit represents concepts which identify and model both concrete and abstract entities (Wang, 2015b).

COMPARISON OF KNOWLEDGE BASE MODELING APPROACHES

According to the analysis carried out in Bimba et al. (2016), some key findings that compare the various knowledge base modeling approaches are shown in Table 1. This comparison was based on the structure, knowledge representation, and limitations of the different approaches to knowledge modeling. The cognitive knowledge base structure comprises of a logical model, a linguistic knowledge base, and an OAR which is similar to the attribute, values, and relations of concepts in an ontology. These attributes allow the cognitive knowledge base to utilize the advantages of these approaches. The process of acquiring knowledge in a cognitive knowledge base is fully automated, unlike the expert knowledge base, ontologies, and linguistic knowledge base. This makes the process of eliciting knowledge less cumbersome. The cognitive knowledge base does not depend on volatile expert knowledge. One of the main characteristics of m-learning is instant access to information and student's active participation and collaboration. To efficiently elicit knowledge in the m-learning system an autonomous, less cumbersome approach is required. Furthermore, to represent accumulative and dynamic knowledge, a non-static form of representation is necessary. Based on the characteristics of knowledge in m-learning system, the cognitive knowledge base is proposed for eliciting and representing knowledge in the m-learning system.

Table 1: Comparison of Knowledge Base Modeling Approaches. (Bimba et al., 2016)

Knowledge Base Technology	**Structure**	**Knowledge Representation**	**Limitations**
Linguistic Knowledge Base	Frames, some lexical semantic associations between *synsets,* and graphs.	Frame elements, Concept map, a semantic network and semantic graph.	Dependence on volatile expert knowledge, difficult and expensive to build, Shallow coverage of human knowledge.
Expert Knowledge Base	The linguistic object, value, and operator.	IF-THEN rules.	Difficulty in capturing expert knowledge, Brittleness of rules, Difficulty maintaining large rule-base, Inference efficiency problem.
Ontology	Classes, relations, and instances.	Taxonomy of concepts with their attributes, values, and relations.	Difficulty in capturing expert knowledge, Lack of sufficiently validated and generalized development methodology.
Cognitive Knowledge Base	Consist of the logical model, physical model, linguistic knowledge base and knowledge manipulation engine.	Object-attribute relation (OAR) model based on concept algebra.	Fewer development tools and implementations in comparison with other knowledge representation technologies.

COGNITIVE KNOWLEDGE-BASED M-LEARNING FRAMEWORK

In an m-learning environment, knowledge can be represented in the form of models. The three most important models are the student model, the domain model, and the pedagogical model. The student model represents information about the user's current knowledge of the domain, profile, cognitive style, learning style, emotional state, learning style, errors made, misconceptions, response to feedback, etc. (Carmona & Conejo, 2004; Kazanidis & Satratzemi, 2007; Luckin & Holmes, 2016). This information determines the characteristics of the student and the interaction with the domain and pedagogical models.

On the other hand, the pedagogical model represents the knowledge and expertise of teaching. Specific knowledge represented in the pedagogical model includes effective teaching techniques (deductive and inductive), the various instructional methods (lectures, problem-based learning, inquiry learning etc.), the instructional plans that define phases, roles and sequence of activities (Scheuer, Loll, Pinkwart & McLaren, 2010), feedback types (depending on a student's action), and assessment to inform and measure learning (Luckin & Holmes, 2016).

The domain model represents knowledge of the subject being learned. It mainly consists of concepts such as how to add, subtract, multiply numbers; newton's law of motion; how to structure an argument; and different approaches to reading. (Luckin & Holmes, 2016). The size of the domain knowledge which represents concepts can differ between m-learning systems, according to the domain size, application area, and the choice of the designer (Kazanidis & Satratzemi, 2007).

The effectiveness of a knowledge management system is based on the technique used in representing knowledge (Duan, Wu, & Ye, 2013). The cognitive knowledge base is a structure that manipulates knowledge as a dynamic concept network like the human knowledge processing (Wang, 2008; Wang, Tian & Hu, 2011). In CKB a concept is a cognitive unit which identifies and models real-world concrete entities and a perceived world (abstract entity) (Wang, 2015a). This work proposes a knowledge representation technique according to concept algebra and uses it for student modeling in mobile learning. This approach enables a richer semantic capability. Concept algebra is concerned with the study of relationships between concepts. It offers 9 different algebraic relations, which include the following: instantiation, extension, inheritance, aggregation, substitute, tailoring, decomposition, composition, and specification (Wang, 2006). These relationships encompass most algebraic relationships between concepts and make the description of knowledge explicit. By imitating the characteristics of the brain neurons, Wang (2007) proposed a way to represent internal knowledge using the OAR model shown in Equation 1.

$$c \,\Delta\, (O, A, R^c, R^i, R^o) \qquad (1)$$

where

- O is a nonempty set of an instance of the concept, $O = o_1, o_2, ..., o_m = ÞU$, where $ÞU$ denotes a power set of U
- A is a nonempty set of attributes, $A = a_1, a_2, ...a_n = ÞM$
- $R^c \subseteq O \times A$ is a set of internal relations.
- $R^i \subseteq C' \times C$ is a set of input relations, where C' is a set of external concepts.
- $R^o \subseteq C \times C'$ is a set of output relations. (Wang, 2014)

The object O is a perception of an external entity or an internal concept which is usually referred to as the extension of the concept. An attribute or intentions of a concept is a sub-object that defines the attributes and characteristics of an object. The relations represent both internal and external connections of a concept. R^c represents a set of internal relations between pairs of object-object, object-attribute, attribute-attribute. R^i represents an external input relationship between a concept and another concept within the knowledge base. While R^o signifies an external output relationship between a concept and another concept within the knowledge base.

Using concept algebra, the proposed m-learning model aims at developing a student model that will allow a proper establishment of the internal relationship between the characteristics of a student and an external relationship with the target domain and pedagogy. The objective is to resolve the pedagogical challenges in m-learning by aiding student metacognition through a model of a student with the target domain and pedagogy. The proposed framework allows a proper categorization of students to support collaborative learning in a social platform by utilizing the strength of m-learning. The details of the proposed framework are presented in the next sub-sections.

The Proposed M-Learning Framework

The m-learning framework proposed here is based on the cognitive knowledge base introduced by Wang (2014). The two main modules of the framework are the knowledge manipulation engine and the cognitive knowledge base as shown in Figure 1. During knowledge acquisition, a concept is selected from the input information. Based on the knowledge acquisition algorithm, the attributes of the extension of that concept is acquired from the linguistic knowledge base (LKB). The linguistic database defines the concept attribute space. The internal relationship is established with the acquired intentions of the concept. The aim of the knowledge acquisition is to retain a newly acquired knowledge as a formal concept as shown in Equation 1.

Once the internal relationship of a concept is determined, the knowledge bonding process begins. It creates relational links between the newly acquired concept and existing concepts in the knowledge base. The knowledge bonding algorithm uses comparative analysis to establish a 1-to-n mapping of newly acquired concept and other matching concepts in the CKB. The object, attribute, and internal and external relations will be used to decide to which layer the new concept belongs in the physical database once it is determined. Finally, the logical database retains the established formal concept represented as an OAR model.

In complex settings, these concepts can have relationships with each other, resulting in a conceptual network representing the entire knowledge of the student as represented in the physical knowledge base in Figure 1. Common relationships used by most systems include *prerequisite* (where the student has to know the first concept before studying the next related concept), *is-a* (where a concept is an instance of another concept), and *part-of* (where a concept is part of another concept) (Kazanidis & Satratzemi, 2007; Virvou & Tsiriga, 2001). The student model represents the student's knowledge of the domain, individual characteristics, and personal interactions with the mobile device (Kazanidis & Satratzemi, 2007; Luckin & Holmes, 2016).

The knowledge retrieval process allows users (students) to access the acquired knowledge obtained in the cognitive knowledge base. The framework supports retrieval of a student group based on the relationships between students (concepts). This information allows students to view their knowledge in relation to other similar students. It also provides a view for students to retrieve their cognitive state by providing a relation between them and the target domain and pedagogy.

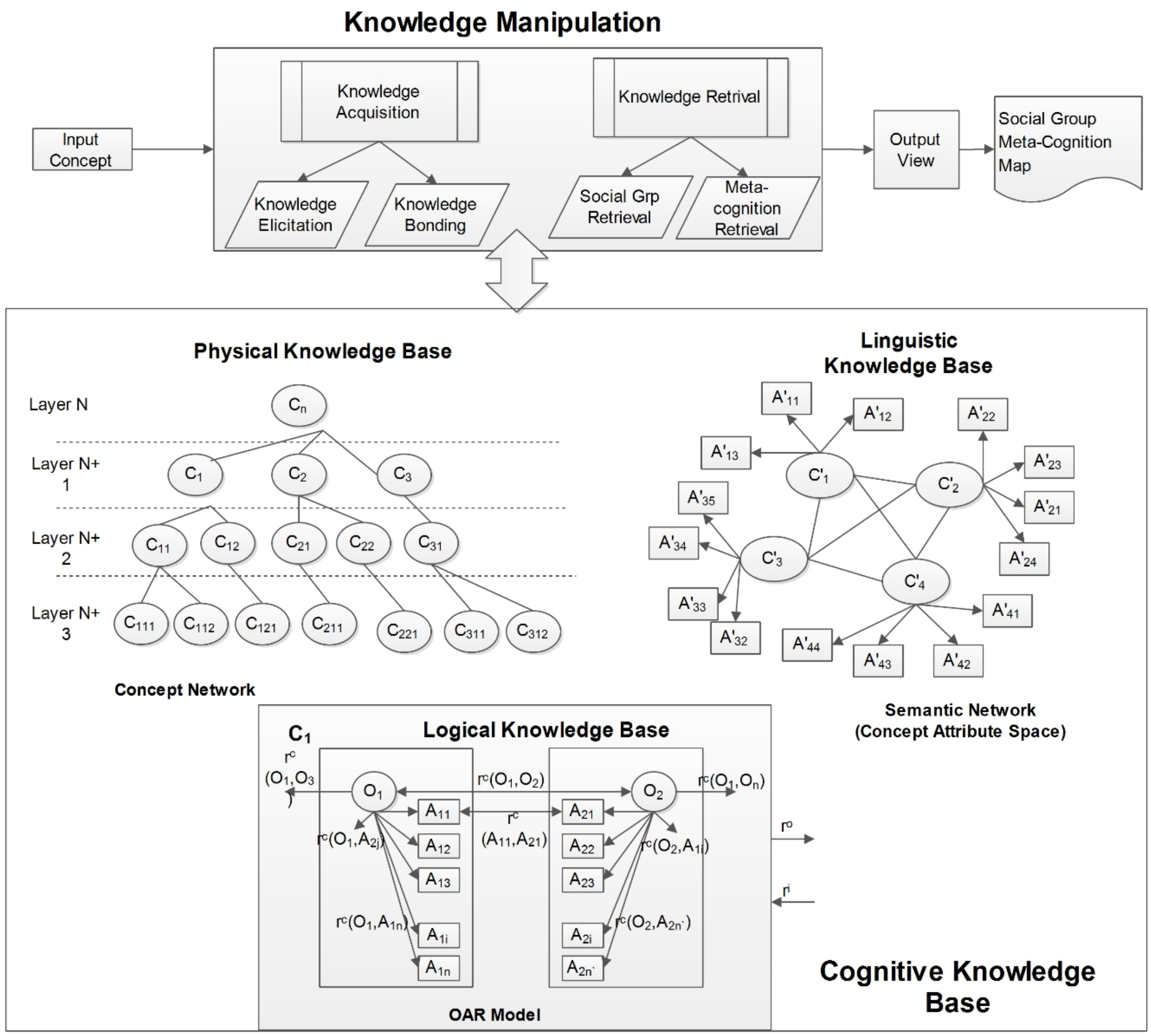

Figure 1: Cognitive Knowledge-based Framework for M-Learning.

ALGORITHMS FOR KNOWLEDGE MODELING AND MANIPULATION IN M-LEARNING

Knowledge acquisition and extraction are the two main processes in the proposed cognitive knowledge-based framework. The knowledge acquisition phase involves the knowledge elicitation and knowledge bonding algorithms. The social group mapping and meta-cognition algorithms are used in the knowledge extraction phase.

Knowledge elicitation algorithm

According to the structure of the cognitive knowledge base, we propose an optimized representation of the concept in a pedagogical, domain, and student model. Firstly, all information in this models is viewed as concepts. As shown in Figure 1, the knowledge acquisition phase assumes a perfect concept attribute (CA) space that represents the linguistic knowledge base as a semantic network. The CA space consists of concepts and their corresponding attributes. The input to the knowledge elicitation algorithm is a concept, which is represented as a 5-tuple $C\,\Delta\,(O, A, R^c, R^i, R^o)$ here are the main steps in Algorithm 1:

Data: C_n
Result: $\{O, A \subseteq (A_1, A_2, A_3 ... A_n), R^c, null, null\}$, C_n category, C_n index, time stamp
initialization;
while *C_n is available* **do**
    Determine C_n category (pedagogy, student or domain);
    if *C_n category = student* **then**
        read multiple C_n;
        C_n = multiple C_n;
    else
        read C_n;
    end
    if *!(Knowledge base full)* **then**
        search LCB for attributes;
        compare *Cn* attributes with existing concepts;
        if *(Full concept match)* **then**
            return (concept exists!);
        else
            assign an index to *Cn*;
            generate acquisition time stamp ;
            calculate $Rc \subseteq O \times A$;
            determine partial concept
            $C = \{O, A \subseteq (A1, A2, A3 ... An), Rc, null, null\}$;
            output $\{O, A \subseteq (A1, A2, A3 ... An), Rc, null, null\}$,*Cn* category, *Cn*
            index, time stamp;
            end
        else
        return (Knowledge base full!);
    end
end

Algorithm 1: Knowledge Elicitation Algorithm

At this stage the external relationship between the newly acquired concept C_n, R^i *and* R^o are yet to be determined. These relations will be updated by existing concepts in the knowledge base through the knowledge bonding process.

Knowledge bonding algorithm

In the second phase of knowledge bonding, the algorithm creates subordinate relations between the newly acquired concept and all other concepts which exist in the cognitive knowledge base. The matching analysis and blending of the new concept C_n to the CKB model is through comparative analysis as described in the knowledge bonding algorithm. The input to the knowledge bonding process comprises of O, $A \subseteq (A_1, A_2, A_3 ... A_n)$, R^c, null, null, C_n category, C_n index, time stamp. The output of the knowledge bonding algorithm is the newly acquired concept, incorporated in the CKB model.

The index number of the new concept C_n is obtained by incrementing the index number of the last concept C_{n-1} entered in the knowledge base by the knowledge elicitation algorithm. While establishing external relationships, the knowledge bonding algorithm carries out five conditional checks (similarity type, St) against each concept C_i available in the knowledge base. First, the similarity check identifies sub-concepts between the new concept C_n and the i^{th} concept in the knowledge base $A_i \subseteq A$. In this state the intentions of the current concept C_i is a subset of that of the new concept C_n. The second check matches the new concept to super-concepts within the knowledge base, where the intentions of the new concept is a subset of the existing concept. The related concepts are identified in the third check. The intersection of the intentions of C_i and C_n is not null, $A_i \cap A \neq$ null. In the fourth check, independent concepts are designated as a null intersection between the intentions of C_i and C_n. The last check determines the similar concepts by matching the intentions of C_i and C_n. The index of the i_{th} concept in the database and the type of similarity St are recorded as the similarity index once a related match has been found. Finally, the layer of abstraction of the new concept is determined and stored together with the aggregated relationships R^o, R^i, the similarity index and all input parameters to the knowledge bonding algorithm as a fused concept in the cognitive knowledge base.

Data: $\{O, A \subseteq (A_1, A_2, A_3 \ldots A_n), R^c, null, null\}$, C_n category, C_n index, time stamp
Result: $\{O, A \subseteq (A_1, A_2, A_3 \ldots A_n), R^c, R^i, R^o\}$, C_n category, C_n index, time stamp, C_n layer, Similarity index $S \subseteq \{(C_i, St_k),(C_{i+1}, St_{k+1}),(C_{i+2}, St_{k+2})\ldots\}$
read C_n;
while *(C_i is available in CKB)* **do**
compute $R_i^o = C_n \times C_i$;
compute $R_i^i = C_i \times C_n$;
compute similarity $C_n \sim C_i = \left|\frac{A \cap A_i}{A \cup A_i}\right|$;
$$= \begin{cases} 1 & C_n = C_i \\ (0,1) & C_n \leftrightarrow C_i \lor C_n < C_i \lor C_n > C_i; \\ 0 & C_n \neq C_i \end{cases}$$
Determine sub-concept $A_i \subseteq A$;
Determine super-concept $A \subseteq A_i$;
Determine related-concept $A_i \cap A$;
Determine independent-concept $A \cap A_i$;
Determine equivalent-concept $A_i = A \land O_i = O \land R^c = R_c^i$;
Determine similarity type St ;
Similarity index $S_i \subseteq \{(C_i, St_k),(C_{i+1}, St_{k+1}),(C_{i+2}, St_{k+2})\ldots\}$;
$S = S + S_i$;
$R^o = R^o + R_i^o$;
$R^i = R^i + R_i^i$;
end
determine C_n layer;
enter concept C_n : $\{O, A \subseteq (A_1, A_2, A_3 \ldots A_n), R^c, R^i, R^o\}$, C_n category, C_n index, time stamp, C_n layer, Similarity index $S \subseteq \{(C_i, St_k),(C_{i+1}, St_{k+1}),(C_{i+2}, St_{k+2})\ldots\}$;

end

Algorithm 2: Knowledge Bonding Algorithm

Knowledge extraction is the second process in the proposed cognitive knowledge-based framework for m-learning. It enables students to access the elicited knowledge obtained by the knowledge acquisition algorithms. The retrieval operations allow the student to view themselves as a subset of a social group which comprises of students with similar intentions. It also allows the student to view their progress by determining the relationship between various learning sessions, providing a metacognitive view of their learning process.

Social group mapping algorithm

M-learning is based on the mobility of students across time, space, and content. The ability to have instant access to information and colleagues requires the need for providing effective collaboration and interaction in m-learning applications. The purpose of the social group mapping algorithm is to provide a common effective platform for students to interact and collaborate with their subordinates, equivalents, and superiors while learning. The social group mapping algorithm searches a target equivalence, sub, and super concept group to which a target student belongs. The similar group reveals a set of students with same knowledge level; the subgroup signifies a student group that can be mentored by the target student and the super group where the target student can request mentoring. This approach utilizes the content-addressed mechanism of a CKB for knowledge retrieval and manipulation which is enabled by the cognitive search algorithms and structural models. As shown in Algorithm 3, the social group mapping algorithm searches the CKB for a target similar concept. If any of the target concepts are found, all related concepts are retrieved based on corresponding indexes registered during the concept acquisition phase. Each of the concepts retrieved (student) are represented as either a group of mentees S_c, mentors S^c or equivalents E_c in respect to the target student.

Data: *TargetStudentAttribute A, Sim Threshold TH*
Result: *ConceptFound* C_f, *Mentee Group* S_c, *Mentor Group* S^c , *Equivalent Group* E_c)
C_f =false;
S_c=null;
S^c=null;
E_c=null;
while (C_i *is available*) **do**
  if (!(C_f) **then**
    compute similarity $C_n \sim C_i = \left|\frac{A \cap A_i}{A \cup A_i}\right|$;
    $= \begin{cases} 1 & C_n = C_i \\ (0,1) & C_n \leftrightarrow C_i \lor C_n < C_i \lor C_n > C_i; \\ 0 & C_n \neq C_i \end{cases}$

    if *(Cn ~ Ci > TH)* **then**
    C_f =true;
    Retrieve all sub-concept of C_i;
    $S_c \subseteq (S_{c1}, S_{c2}, S_{c3}...S_{cn})$;
    Retrieve all equivalent of C_i;
    $E_c \subseteq (E_{c1}, E_{c2}, E_{c3}... E_{cn})$;
    Retrieve all super-concept of C_i;
    $Sc \subseteq (S^{c1}, S^{c2}, S^{c3}...S^{cn})$;
    exit loop;
    end
  end
end
if C_f **then**
  output (*ConceptFound Cf, Mentee Group Sc, Mentor Group Sc, Equivalent Group Ec*);
else
  output 'No social group identified!!!';
end

Algorithm 3: Social Group Mapping Algorithm

Student meta-cognition algorithm

One of the challenges of m-learning is the lack of support for improving meta-cognitive skills. Although students can measure their performance against a predefined plan, they are not provided with the ability for self-assessment. Students need to view their learning process with the capacity to judge how much they have done and the new knowledge acquired.

The student metacognition algorithm involves the presentation of student's incremental knowledge based on learning goals and learning sessions. Every student learning session (LS) is modeled as a concept in the knowledge acquisition phase. All activities performed by a student, domain, and pedagogical knowledge interaction are elicited as attributes or intentions of the learning session. The student meta-cognitive algorithm retrieves student's learning session based on incremental and decremental relationships. This enables the student to understand the learning process and provides knowledge about the student's cognitive process. As shown in Algorithm 4, the input to this process is the target student learning session and a time stamp indicating the oldest learning session for comparison. The output is the cognitive process, indicating student learning processes. Based on algorithm 4, the student meta-cognitive algorithm searches the CKB for the various learning sessions (LS) of a specific student. A learning session is identified through a similarity match between the current student learning session (S) and the i^{th} previous learning session of that student. Once a learning session belonging to the target student (S) is identified, the type of similarity is then determined. The matched student learning session consisting of the acquired time stamp, similarity type in respect to the target student session, student's interaction with the domain and pedagogical knowledge is then added to the student cognitive process (CP). This process continues iteratively until all sessions after the specified timestamp is exceeded.

Data: *TargetStudent S, Timestamp T*
Result: *CognitiveProcess* $CP \subseteq ((LS_i, SimT, T_i), (LS_{i+1}, SimT, T_i), (LS_{i+2}, SimT, T_i), \ldots (LS_n, SimT, T_i))$
CP =null;
C_f =false;
while *(LS_i Timestamp > T) is available* **do**

compute similarity $S \sim LS_i = \left|\frac{A \cap A_i}{A \cup A_i}\right|$;

$$=\begin{cases} 1 & S = LS_i \\ (0,1) & S \leftrightarrow LS_i \lor S < LS_i \lor S > LS_i; \\ 0 & S \neq LS_i \end{cases}$$

if $S \sim SL_i$ **then**

C_f =true;
Determine relationship type *SimT* ;
Retrieve SL_i Timestamp T_i;
CP = CP + (LS_i, *SimT* ,T_i);

end

end
if C_f **then**
Output CP;
else
Output No Learning Session Found!!! ;
end

Algorithm 4: Student Meta-Cognition Algorithm

DISCUSSION

The design and implementation of an effective m-learning application are challenging, due to the reliance on both pedagogical and technological elements. To tackle this challenge, frameworks which describe the conceptual interaction between the various components of pedagogy and technology have been proposed. Koole's (2009) framework focused on addressing the issue of information overload, knowledge navigation, and collaborative learning, while Sha et al. (2012) proposed self-regulatory learning in mobile learning. In a m-learning environment, students have little feedback on the learning material and educational process, thus, resulting in confusion in setting up learning goals and understanding the learning gains. Meta-cognition, which is the ability for students to be aware of their learning process, helps them to manage their knowledge acquisition process. One key advantage of mobile learning is the capacity to have instant access to information and colleagues across time, space, and content. This raises a need to establish relevant and efficient collaborative groups within an m-learning environment.

This research proposes a framework for social and meta-cognitive support to tackle the issues raised. Two algorithms are introduced, the meta-cognition algorithm for representing the student's learning process, which is capable of providing a means for self-assessment, and the social group mapping algorithm for classifying students according to social groups. The meta-cognitive algorithm provides the students with a view of their learning process and ability to judge their effort and newly acquired knowledge. A common and efficient platform for students to interact is provided by the social group mapping algorithm. A cognitive knowledge base is proposed based on the shortcomings of traditional knowledge representation techniques as discussed in an earlier section. The CKB considers concepts as a cognitive unit which models a real-world entity. This technique uses concept algebra to model the student within the m-learning environment. CKB has a rich semantic capability, which provides various relationships between concepts.

The effectiveness of any knowledge management system is grounded in the technique used in representing the knowledge. The CKB proposed, manipulates knowledge as a dynamic concept network, similar to human knowledge processing. M-learning designers can utilize the proposed framework for providing meta-cognition and social support within an m-learning environment. M-learning developers can implement the algorithms proposed and provide a platform for instructors and educationist to invent new pedagogical practices and evaluate its effectiveness in an m-learning environment.

Conclusion and Future Direction

M-learning provides tremendous benefits such as mobility, instant access to information, connectivity, social interactivity, and the flexibility of time, place, pace, and space. However, current implementations provide little knowledge of the delivery of learning materials and the educational process (Ebrahim et al., 2015). This lack of external feedback to students causes confusion about learning goals and gains. In this research, a cognitive knowledge representation technique is proposed to support the elicitation of student knowledge during learning, providing a means for self-assessment and judging newly acquired knowledge. Furthermore, the strength of m-learning in supporting social interactivity is utilized to provide a social platform for collaborative learning. The cognitive knowledge base approach is proposed based on its ability to autonomously acquire and represent accumulative and dynamic student knowledge in m-learning.

Using concept algebra, the proposed m-learning model aims to develop a student model that will allow a proper establishment of the internal relationship between the characteristics of a student and an external relationship with the target domain and pedagogy. The objective is to resolve the pedagogical challenges in m-learning by aiding student metacognition through a model of the student with the target domain and pedagogy. Utilizing the strength of m-learning in a social context, this technique allows a proper categorization of students to support collaborative learning in a social platform.

We proposed a cognitive knowledge-based framework for m-learning which is based on concept algebra initiated by Wang (2014). It comprises of two main modules: knowledge manipulation engine and the cognitive knowledge base. The process of acquiring and presenting knowledge in the proposed framework depends on four algorithms: knowledge elicitation, knowledge bonding, social group mapping, and meta-cognition algorithms. The main contribution of this work is the presentation of the social group mapping and metacognition algorithms. The purpose of the social group mapping algorithm is to provide a common platform for students to interact and collaborate with their subordinates, equivalent, and superiors while learning. The student meta-cognitive algorithm retrieves a student's learning session based on incremental and decremental relationships. This enables the student to understand the learning process and provides knowledge about the student's cognitive process. This model is envisaged to serve as a guide for developers in implementing suitable m-learning applications. Furthermore, educationists and instructors can devise new pedagogical practices based on the possibilities provided by the proposed m-learning framework.

In the future, the proposed framework will be evaluated against some set of criteria for its effectiveness in acquiring and presenting knowledge in a real-life scenario. By analyzing real student interaction in m-learning, the algorithms will be tested to show their applicability in eliciting student metacognition and support for social interactivity. Furthermore, the framework can be refined or extended to resolve other m-learning challenges.

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